The Effect of Vacant Building Demolitions on Crime under Depopulation

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Abstract

The United States government spent almost $200 million on vacant building demolitions between 2008 and 2011 under the Neighborhood Stabilization Program alone.[2] One of the main justifications for these demolitions is that they reduce the crime caused by vacant buildings.[3] However, no clear causal link has been established between residential vacant building demolitions and crime, nor has it been determined whether demolitions decrease crime globally or merely displace it into other areas within a city. I examine these questions using block level monthly panel data from Saginaw, Michigan to estimate a Poisson fixed effects model. To control for the endogeneity of crime and demolitions, I compare changes in crime after a demolition to changes in crime during the permit period before a demolition after which point the timing of the demolition is not dependent on crime but rather on administrative procedures. I also analyze the spatial impacts of demolitions through a spatially lagged independent variable model. Results indicate that once endogeneity is controlled for, demolitions do cause a reduction in property crime at the block level but that they cause an increase in violent crime in blocks surrounding the demolition and they have little aggregate effect on crime in the census tract as a whole. This suggests that demolitions do not reduce crime overall but rather displace it from the block of the demolition into other blocks within the city.

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[2] United States Department of Housing and Urban Development, 2011
[3] Eastern Pennsylvania Organizing Project and the Temple University Center for Public Policy, 2001; The Community Research Partners and Rebuilt Ohio, 2008

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1 Introduction

The durability of housing has been found to be the primary reason why urban decline is more persistent than growth.[4] Because houses are not removed as quickly as they are built, negative shocks decrease housing prices more than they decrease population, which leads to a slower change than does a positive shock. Demolitions may be one way to counteract this durability. However, little research exists on the effects of demolitions or on vacancies in general.[5]

Policy makers and academics argue that one link between vacant buildings and depopulation is crime.[6] Not only does crime cause depopulation and vacant structures,[7] but vacant structures cause crime through increased incidences of arson, the sheltering of criminals, and the creation of general disorder.[8] With this as a central justification, the United States Government spends millions of dollars a year demolishing vacant buildings. Between 2008 and 2011, the government spent almost $200 million on vacant building demolitions under the Neighborhood Stabilization Program, which is only one of several funding sources for demolitions.[9] The city of Flint, Michigan alone was awarded over $3 million in 2010 -- the same year in which the number of murders in the city reached an all-time high.[10] In fact, the city budget was so constrained that year that the jail was shut down and as a result, police officers had to issue tickets rather than arrest warrants for many offenses.[11] Are demolitions the best use of funding in such economically and fiscally stressed cities?

This paper attempts to answer part of this question by examining the relationship between demolitions and crime. Although previous research has shown a causal link between high-rise public housing demolitions and crime,[12] no research has established a causal link between residential vacant building demolitions and crime. In this paper, I fill this gap by estimating the causal and spatial impact of demolitions on crime. To do this, I use block level monthly panel

[4] Glaeser and Gyorko, 2005
[5] Schilling and Logan, 2008
[6] In this paper, I use the term "vacant" to refer to blighted or dangerous buildings. Not all of the buildings that are demolished are technically vacant. Some still have residents living in them but are dangerous enough for the city to have the power to demolish.
[7] Cullen and Levitt, 1999
[8] Winthrop and Herr, 2009; Spelman, 1993; Eastern Pennsylvania Organizing Project and the Temple University Center for Public Policy, 2001; The Community Research Partners and Rebuilt Ohio, 2008
[9] United States Department of Housing and Urban Development, 2011
[10] HUD NSP Snapshot, 2010
[11] For more serious offenses, Flint police officers use the county jail if there is space.
[12] Hartley, 2010

data from Saginaw, Michigan from January 2008 through June 2009 to estimate a Poisson fixed effects model. To estimate the causal effect, I compare only those blocks that have undergone a demolition in a given month to those that are permitted for a future demolition.[13] The key assumption for the exogeneity of demolitions and crime is that demolitions are not correlated with unobserved factors that may influence the change in crime rates. This may not be true. Vacancies and, consequently, demolitions are more likely to occur in areas where crime rates are increasing. In addition, the way in which a house gets placed on the demolition list may be correlated with unobserved factors that are also correlated with changes in crime. Residents may be more likely to report a vacant building in their neighborhood if they live in an area with increasing crime.

However, once a house is put into the process of being permitted for a demolition, the timing of the demolition is not dependent on changes in crime but rather on the administrative process of filling in the paperwork, passing asbestos and historical checks, and making contact with the owners of the building. I exploit this timing by comparing the change in crime after a demolition to the change in crime during the permit period. This allows me to estimate the causal impact of demolitions on crime. I also examine the spatial impacts of demolitions on crime through use of a spatially lagged independent variable model to determine whether crime is affected on the block, in the neighborhood, and/or in the census tract as a whole.

There are two related mechanisms that may cause a demolition to affect crime. The first is crime displacement, in which a demolition merely causes crime to be relocated into another part of the city or causes a criminal to switch to a different type of crime because the building in which they were committing crime is no longer present. This may cause crime to decrease or switch types on the block of the demolition, but to increase in other areas of the city. A related mechanism that might cause aggregate crime to decrease is related to the broken windows hypothesis, which implies that the general disorder caused by a vacant building encourages crime not only on that property but in the neighborhood in general. If a vacant building is demolished, then the disorder is diminished and positive spillovers occur in which crime is reduced not only on the block in question, but in the neighborhood and perhaps in the city as a whole.

[13] In this paper, I use the term "permit" to refer to the point in time at which the demolition process is put into motion. This "permit" period can be anywhere from zero to 17 months in my data set.

Previous research has found that vacant land and buildings are correlated with increased levels of crime, with estimates ranging from $1,472 of public safety money spent per vacant property[14] to a doubling of crime rates on blocks with open abandoned buildings.[15] Immergluck and Smith (2005) look at foreclosures rather than at vacant buildings and find that a one standard deviation increase in foreclosure rates (about 2.8 foreclosures per 100 owner-occupied properties) leads to a 6.7% increase in violent crime but has no impact on property crime.[16]

Policy papers also argue that vacant land contributes to increased crime. These authors argue that vacant buildings and lots attract trash and debris, are used as drug dens, and are targeted by arsonists.[17] They cite stories from residents saying that "there is more crime" since blight took over[18] and from city officials who say that, in their experience, vacant buildings are "magnets for crime."[19]

However, crime may also cause properties to become vacant, making it difficult to determine the causal effect of vacancies on crime. Demolitions may also not be randomly chosen and may occur on blocks that have higher levels and trends of crime. Some cities strategically choose to demolish vacant buildings in specific neighborhoods in order to rehabilitate that area. This choice may be correlated with crime.

Some researchers have found innovative ways to account for this endogeniety in the case of high rise public housing demolition. Jacob (2003) utilizes a plausibly exogenous source of variation in housing assistance generated by public housing demolitions in Chicago to examine the impact of high-rise public housing on student outcomes, finding that children in households affected by the demolitions do no better or worse than their peers, a result contradictory to much of the literature. Hartley (2010) compares public housing buildings that are scheduled for demolition to those that have undergone demolition and finds that public housing demolitions are associated with a 10 to 20 percent reduction in murder, assault, and robbery in neighborhoods where the demolitions occurred. I utilize a similar quasi-experimental approach in which I compare the changes in crime after a demolition to the changes in crime during the permit period for the demolition. Because the timing of demolitions within the permit list is not correlated

14 Winthrop and Herr, 2009
15 Spelman, 1993
16 Immergluck and Smith, 2005
17 The Community Research Partners and Rebuilt Ohio, 2008
18 Eastern Pennsylvania Organizing Project and the Temple University Center for Public Policy, 2001
19 The Community Research Partners and Rebuild Ohio, 2008

with changes in crime, this method removes the endogeneity caused by the choice of whether to demolish each house.

A second issue that arises when analyzing the impact of demolitions on crime is whether crime actually disappears when a house is demolished or whether it is displaced into to another area within the city. If it is simply displaced, then demolitions do not impact the overall level of crime in a city. Bowers and Johnson (2003) use a weighted displacement quotient to measure the spatial effects of crime prevention activities. They compare what occurs in a buffer zone around prevention activities and relate it to changes in the target area. I utilize a variation of this technique in which I estimate the effect of demolitions on the block, in the block group, and in the census tract simultaneously in order to determine whether, holding demolitions on the block constant, demolitions on a nearby block affects crime on the block in question. Displacement effects appear to only occur within the block group, indicating that displacement between census tracts is unlikely. Therefore, I only aggregate up to the census tract level.

Empirically, I improve upon the previous research in four ways. First, I directly analyze the impact of demolitions on crime rather than the impact of vacancies on crime which may not be equivalently opposite. Social disorganization theory states that social capital and cohesion are disrupted when a neighborhood loses population because the social controls that had put limits on criminal activity are deteriorated.[20] Demolishing a house will not counteract this effect and may even exacerbate it if the house was not vacant to begin with.

Second, I use block level panel data, which allows me to control for unobserved heterogeneity through use of a Poisson fixed effects model. I also estimate the average partial effect of these Poisson estimates by averaging out over the unobserved heterogeneity rather than assuming that it is zero as is common with current data analysis and statistical software.

Third, I determine the causal impact of demolitions on crime by controlling for endogeneity with a quasi-experimental design in which the changes in crime after a demolition are compared to the changes in crime during the demolition permit period. Due to the structure of the demolition policy in Saginaw, I cannot directly measure the effect of demolitions on arson: when a house undergoes arson it is immediately demolished, providing a direct source of endogeneity in my data. In addition, anecdotal evidence suggests that this policy has incentivized neighbors of vacant buildings to commit arson against the vacant building in order

[20] Park and Burgess, 1925; and Shaw and McCay, 1931, 1942, 1969

to get the house demolished more quickly. However, I can estimate the causal impact of demolitions on all other types of crime.

Fourth, I analyze the spatial impacts of demolitions on crime through use of a spatially lagged independent variable model. This allows me to directly measure the displacement and spillover effects of demolitions on crime on the block, block group, and census tract.

Results indicate that one demolition reduces property crime by 0.678 crimes per year at the block level, increases violent crime by 0.037 crimes per year at the block group level, and has no aggregate effect on crime at the census tract level. This suggests that the reduction in crime at the block level is offset by increases in crime on other blocks, causing an overall null effect. Therefore, demolitions do not reduce overall crime within a city, but merely displace it into other neighborhoods implying that crime reduction is not an adequate justification for demolitions.

2 Conceptual Framework

There are two mechanisms through which demolitions may impact criminal behavior.[21] First, under the rational choice theory of crime, criminals maximize their economic well-being by comparing the benefits and costs of crime such as fines, imprisonment, and social stigmatism.[22] If the potential gain from committing a crime is sufficiently greater than the combined risk of being caught and the size of punishment, then the criminal chooses to commit the crime. Vacant and decrepit buildings and land may signal to potential criminals that the risk of being punished for committing a crime is low, and they may provide shelter that reduces the chance of being caught. This theory implies that demolitions will reduce crime in the immediate area.

This mechanism may cause two types of crime displacement. First, a criminal may choose to commit a different type of crime because he can no longer undergo the activity that he had previously undertaken.[23] For example, if a drug dealer can no longer produce a drug in an abandoned building, he may switch to robbery as a source of income. This theory implies that a demolition will cause a decrease in one type of crime but an increase in another.

Crime displacement may also occur after a demolition if a criminal moves to another location in order to commit the same crime. For instance, the drug producer mentioned

[21] For an excellent review of the crime literature, see Deller, Amiel, and Deller, 2010.
[22] Fleisher, 1963, 1966a, 1966b; Becker, 1968, 1993; and Ehrlich, 1973, 1975
[23] Repetto, 1974

previously may simply move to another vacant building to use as a lab. This theory implies that a demolition will reduce crime in the immediate area but increase it in surrounding areas or on other blocks with vacant buildings.

I analyze this spatial displacement through use of a spatial lag of demolitions in which I examine the effect of demolitions on crime on that same block, demolitions in the block group on crime on the block, and demolitions in the census tract on crime on the block.

The second mechanism through which demolitions may impact crime is through what Wilson and Kelling (1982) term the "broken windows hypothesis." This hypothesis states that if a window in a building is broken and left unrepaired, the rest of the windows in the building will soon be broken as well. Window breaking, they argue, does not necessarily occur on a large scale because some areas are inhabited by determined window-breakers whereas others are populated by window- lovers. Rather, one unrepaired window is a signal that breaking more windows costs nothing.[24] In the case of vacant buildings, the hypothesis implies that one vacant building lying decrepit leads to further crime solely based on the signal that the probability of being punished is low. This suggests that demolitions cause positive spillover effects in which crime is reduced not only in the immediate area but in surrounding areas as well.

This hypothesis was tested by Braga and Bond (2008) through a randomized control trial in Lowell, Massachusetts where they found that targeted policing strategies that attempted to reduce crime through the reduction of disorder and minor offenses ('broken windows') did have a positive effect on reducing overall crime. They found that this effect was strongest when the physical environment was altered, such as when abandoned buildings were removed, rather than when the targeted strategy was misdemeanor arrests. Braga and Bond found no evidence of crime displacement into surrounding areas.

Note that a demolition may not equivalently reduce the crime increase caused by a vacant building for two reasons. First, the social disorganization theory of crime implies that social capital and cohesion are disrupted when a neighborhood loses population and the social controls that put limits on criminal activity deteriorate. Therefore, as land becomes vacant, crime may increase but demolishing houses most likely does not fully counteract this effect. This calls attention to the fact that an increase in crime due to a house becoming vacant may be stronger

[24] Wilson and Kelling, 1982

than the decrease in crime due to the demolition of that house.[25] Therefore, if our policy of interest is demolitions, it is important that we study the effect of demolitions on crime directly rather than solely the effect of vacant buildings on crime. Second, when a building becomes vacant the likelihood of a crime being reported decreases because the number of "eyes" on the street decreases. Vacancies may actually reduce the number of reported crimes. This is not counteracted by a demolition unless a new house is built on the parcel and additional residents move in.

3 Econometric Model

Crime is determined in part by the number of demolitions and the number of vacancies on a block as follows:

$$Crime = f(Demolitions, Vacancies, X_V) \tag{1}$$

Where X_V is a vector of demographic and other relevant characteristics.

However, vacancies and demolitions are also partially determined by crime:

$$\begin{aligned} Vacancies &= f(Crime, Demolitions, X_V) \\ Demolitions &= f(Crime, Vacancies, X_D) \end{aligned} \tag{2}$$

Due to a lack of instruments for use as exclusion restrictions, I do not estimate the system of equations above. Instead, I estimate only the first equation but include a variable for the number of permits in order to compare the effect of a demolition on crime to the effect of a permit on crime which serves as my control group. This will allow me to remove the endogeneity caused by the simultaneity of crime, vacancies, and demolitions and to draw a causal inference. In this way, I exploit both the time variations in demolitions and the lag between when a house gains a demolition permit and when the house is actually demolished.

Therefore, I use the following reduced form equation as a basis for my estimation:

[25] It should be noted that "crime" in this paper consists only of reported crimes and that there may be crimes that go unreported. Reported crimes may increase or decrease due to fewer or more eyes on the streets reporting the crimes.

$$CrimeIncidents_{it} = \beta_1 + \beta_2 demosblock_{it} + \beta_3 permitsblock_{it} + \theta_i + \theta_t + u_{it} \tag{3}$$

Each variable is measured at the block and year level. $CrimeIncidents_{it}$ is the number of crimes on each block in each month, $demosblock_{it}$ is the number of demolitions on each block in each month, and $permitsblock_{it}$ is the number of permits on each block in each month. Block and year fixed effects are represented by θ_i and θ_t respectively. Time invariant variables are captured by the block level fixed effects and are therefore not included in this equation. I also aggregate the data to the block group and census tract level and re-estimate this equation. The difference between β_2 and β_3 will tell me the effect of demolitions on crime compared to the permit period before a demolition.

Although I have data for average property values on the block and the number of occupied parcels (or parcels with buildings on them), I do not include these variables because they are directly caused by my variable of interest which means that they absorb some of the effect of the demolition. I use Huber-White standard errors clustered at the block level. These standard errors are robust to arbitrary forms of error correlation within each block.

I then estimate a spatial model in which I include a spatial lag of demolitions at the block, block group, and census tract levels in order to directly estimate the displacement and spillover effects as follows:

$$\begin{aligned} CrimeIncidents_{it} &= \beta_1 + \beta_2 demosblock_{it} + \beta_3 demosblockgrp_{it} + \beta_4 demostract_{it} + \\ &\beta_5 permitsblock_{it} + \beta_6 permitsblockgrp_{it} + \beta_7 permitstract_{it} + \theta_i + \theta_t + u_{it} \end{aligned} \tag{4}$$

Finally, I perform an event study in which I first cut the sample to only those blocks that undergo a demolition at some point during my time period and then estimate the following equation:

$$CrimeIncidents_{it} = \beta_1 + \sum_{j=-2}^{6+} \beta_j demos_{i,t-j} + \theta_i + \theta_t + u_{it} \tag{5}$$

The last β coefficient is the long run multiplier of the effect of demolitions on crime. I choose an event window of two months before and six plus months following a demolition because the sample size drops outside of this range. I then aggregate my data to the block group and census tract levels and re-run these estimations in order to examine the temporal effects at these different spatial aggregations.

I use levels of crime as my dependent variable rather than the crime rate because no good time-varying estimate of population per block exists in my data set. The only number I could use is the number of occupied parcels on each block. However, this number is defined as the number of parcels with a building on it, not the number of parcels with a person living on it. Therefore, this number changes when a demolition occurs and would cause simultaneity in my estimation. In addition, an occupied parcel could have any number of residents on it, from a single person home to a multi-family rental. Therefore a crime rate based on this number would not only be inaccurate, but would cause bias in my results.

I break incidents of crime into a number of categories in order to measure the effect of demolitions on different types of crime. First, I analyze all types of crime as a whole. Next, I look at violent crime and property crime. Violent crimes include murder and non-negligent manslaughter, forcible rape, robbery, simple assault, and aggravated assault. Property crimes include burglary and breaking and entering, purse snatching, theft from a building, theft from a machine, theft from a vehicle, other larcenies, motor vehicle theft, stolen property, destruction of property, shoplifting, pocket picking, and arson. I further break down all crimes and property crimes into those including arson and those not including arson in order to further explore the endogeneity of demolitions and crime. A house that undergoes arson is immediately demolished, providing a direct source of endogeneity in my data. Examining crimes with arson included and then with it excluded will indicate the sign and significance of the bias.

Because my dependent variable, the number of crimes on a block in a given year, takes on non-negative integer values (is a count variable), a linear model for $E(y \mid \mathbf{x})$ is not ideal because it can lead to negative predicted values.[26] Also, because y can take on the value zero with positive probability, a log transformation is also inappropriate. Therefore, I assume that y_i given x_i takes on a Poisson distribution[27]. The Poisson model is as follows:

[26] Wooldridge, 2002 p 388

[27] Fixed effects estimations in nonlinear models such as this one generally lead to inconsistent estimates. However, the Poisson distribution can be arbitrarily misspecified and any kind of serial correlation can be present and the fixed effects Poisson estimator is consistent under mild regularity conditions (Wooldridge, 2002 p 648). Therefore, a fixed effects model is feasible and appropriate and over dispersion can be ignored.

$$f(y_i) = \frac{e^{-\lambda_i} \lambda_i^{\,y_i}}{y_i!} \quad \text{for } y_i = 0,1,2\ldots \tag{6}$$

where $\lambda_i = e^{x_c\beta} = E(y_i|x_i) = Var(y_i|x_i)$.[28] I specify $x_i\beta$ as in equation (3), (4), and (5).

In order to interpret the coefficients from the Poisson estimations, I follow Verdier (2012) to calculate the partial effect averaged across the population distribution of the unobserved heterogeneity for the coefficients as follows:

$$\begin{aligned} APE_{01}(x_0) &= \int (\exp(c_i + \beta_d + x_0\gamma) - \exp(c_i + x_0\gamma)) dF_{c_i}(c_i) \\ &= (\exp(\beta_d + x_0\gamma) - \exp(x_0\gamma)) \int \exp(c_i) dF_{c_i} \\ &= (\exp(\beta_d + x_0\gamma) - \exp(x_0\gamma)) E(\exp(c_i)) \end{aligned} \tag{7}$$

Where c_i is the unobserved heterogeneity. A consistent estimator for $E(\exp(c_i))$ is found as follows:

$$\begin{aligned} D &\equiv \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{Crime_{it}}{\exp(\beta_d Demos_{it} + x_{it}\gamma)} \\ &= \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\exp(c_i) + \frac{\varepsilon_{it}}{\exp(\beta_d Demos_{it} + x_{it}\gamma)} \\ &\xrightarrow{p} E(\exp(c_i)) \end{aligned} \tag{8}$$

This can be estimated as:

$$\begin{aligned} \hat{D} &\equiv \frac{1}{n}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{Crime_{it}}{\exp(\hat{\beta}_d Demos_{it} + x_{it}\hat{\gamma})} \\ &= D + op(1) \xrightarrow{P} E(\exp(c_i)) \end{aligned} \tag{9}$$

[28] Winkelmann, 2008

Therefore, the APE is as follows:

$$A\hat{P}E_{01}(x_0) = N^{-1}T^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{Crime_{it}}{\exp(\hat{\beta}_d Demos_{it} + x_{it}\hat{\gamma})}(\exp(x_0\hat{\beta} + \hat{\gamma} j_1) - \exp(x_0\hat{\beta} + \hat{\gamma} j_2)) \quad (10)$$

Where j_1 and j_2 are values of demolitions (either zero and one or one and two depending on which APE I am calculating).

As previously mentioned, if demolitions are not randomly chosen but instead are partially determined by crime, $\hat{\beta}_2$ will be inconsistent due to endogeneity caused by selection bias. The key assumption for the exogeneity of demolitions and crime is that demolitions are not correlated with unobserved factors that may influence the change in crime; that $\text{cov}(D_{it}, \varepsilon_{it}) = 0$. Based upon my understanding of the demolition process in Saginaw and analysis of the data, this is not true. For instance, vacancies and therefore demolitions are more likely to occur in areas where crime rates are increasing. In addition, the way in which houses get put on the demolition list may be correlated with unobserved factors that are also correlated with the change in crime in that area. Residents may be more likely to report a vacant building in their neighborhood if they live in an area with increasing crime.

Once a house is put into the process of being permitted for a demolition, however, the timing of the demolition is not dependent on changes in crime but rather on the administrative process of filling in the paperwork, passing asbestos and historical checks, and contacting the owners of the building. As I will show, this administrative process is uncorrelated with either levels of changes in crime in an area. I exploit this timing by comparing only those blocks with a demolition in month *t* to those blocks that are permitted to have a demolition in a future month. This allows me to estimate the causal impact of demolitions on crime.

One additional estimation concern is that shocks to crime before a demolition may revert to the mean during and after a demolition which may cause estimates to appear to be more negative than they actually are. However, event study results show that areas with subsequent demolitions have, before the demolition, lower than average crime levels and thus reversion to the mean from a negative shock to crime could only bias my results in a positive direction. Therefore my results represent the upper bound for the effects of demolitions on crime.

Once a house undergoes any type of fire it is immediately demolished. Because of the direct endogeneity caused by this policy, I cannot include demolitions due to arson in my analysis. There is anecdotal evidence to suggest that this demolition policy is at least in part causing arsons in vacant buildings. Homeowners near vacant buildings have learned that if that vacant building undergoes arson it will be demolished more quickly, which nieghbors perceive as a benefit. Therefore, even without the estimation issues caused by the endogeneity between demolitions and arson, it would be difficult to determine which arsons were caused by vacant buildings themselves and which were caused by the structure of the demolition policy.

4 Data

The data for this study were collected in collaboration with the city of Saginaw's Geographical Information Systems (GIS) Department and its Inspections Department. Block level demographics, property values, vacancy rates, weed abatement and code enforcement were provided by the GIS department, and detailed demolition data, including permit dates, demolition costs, and funders were collected from files within the inspections department. These data provide a unique opportunity to examine the impact of demolitions at a detailed level. Of the related studies, only Winthrop and Herr (2009) use block level data and their analysis is cross sectional. To my knowledge, this is the first study to use block level panel data to examine any issue related to vacant buildings and crime.

There are 1,868 blocks in the city, and the data spans 18 months: January 2008 through June 2009. Therefore, the data consists of 33,624 block-months. Figure 1 shows basic summary statistics for crimes, demolitions, and permits. The crime data is based on the National Incident-Based Reporting System (NIBRS). This reporting method provides an in-depth look at the types of crimes on each block, as well as how many officers reported to the incident and a detailed description of what type of incident occurred.

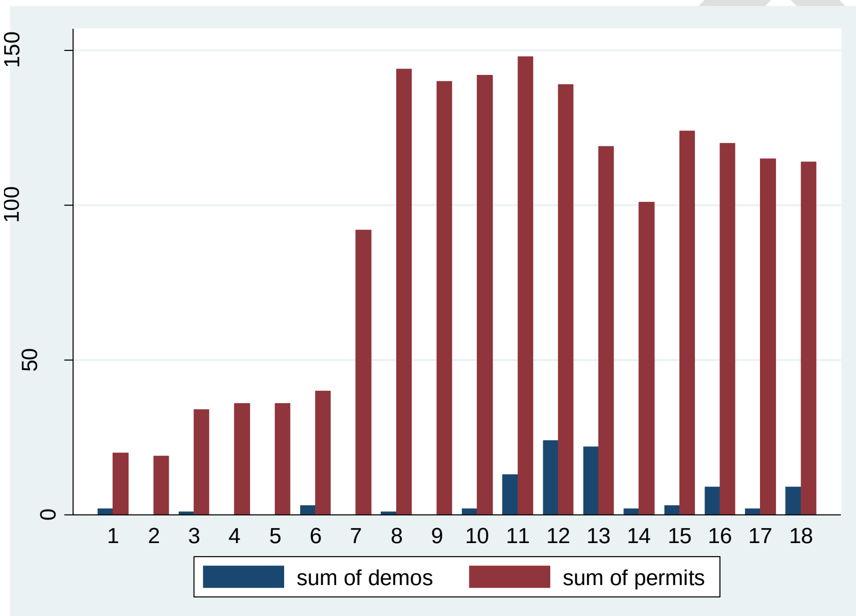
Figure 1: Summary statistics for crimes, permits, and demolitions per block/month

Variable (per block/month)	No. of Obs.	Total	Mean	Std. Dev.	Min	Max
All Crimes	33,642	8,042	0.34	0.85	0	24
Violent Crimes	33,642	1,649	0.11	0.45	0	11
Property Crimes	33,642	3,953	0.15	0.48	0	15

Demolitions	33,664	138	0.00	0.08	0	4
Permits	33,642	112	0.01	0.10	0	4
Permit Time among Permitted Blocks	112	11,121	5.52	4.30	0	17

Figure 2 illustrates the number of demolitions and permits each month in my data set. Month 1 corresponds with January of 2008 and month 18 refers to June of 2009, with consecutive months in between.

Figure 2: Demolitions and permits by month



Only 19 blocks have more than one demolition on them during the time period of my data set. A histogram of blocks, block groups, and census tracts with different numbers of demolitions can be seen in Figure 3.

Figure 3: Histograms of demolitions at block, block group, and census tract levels

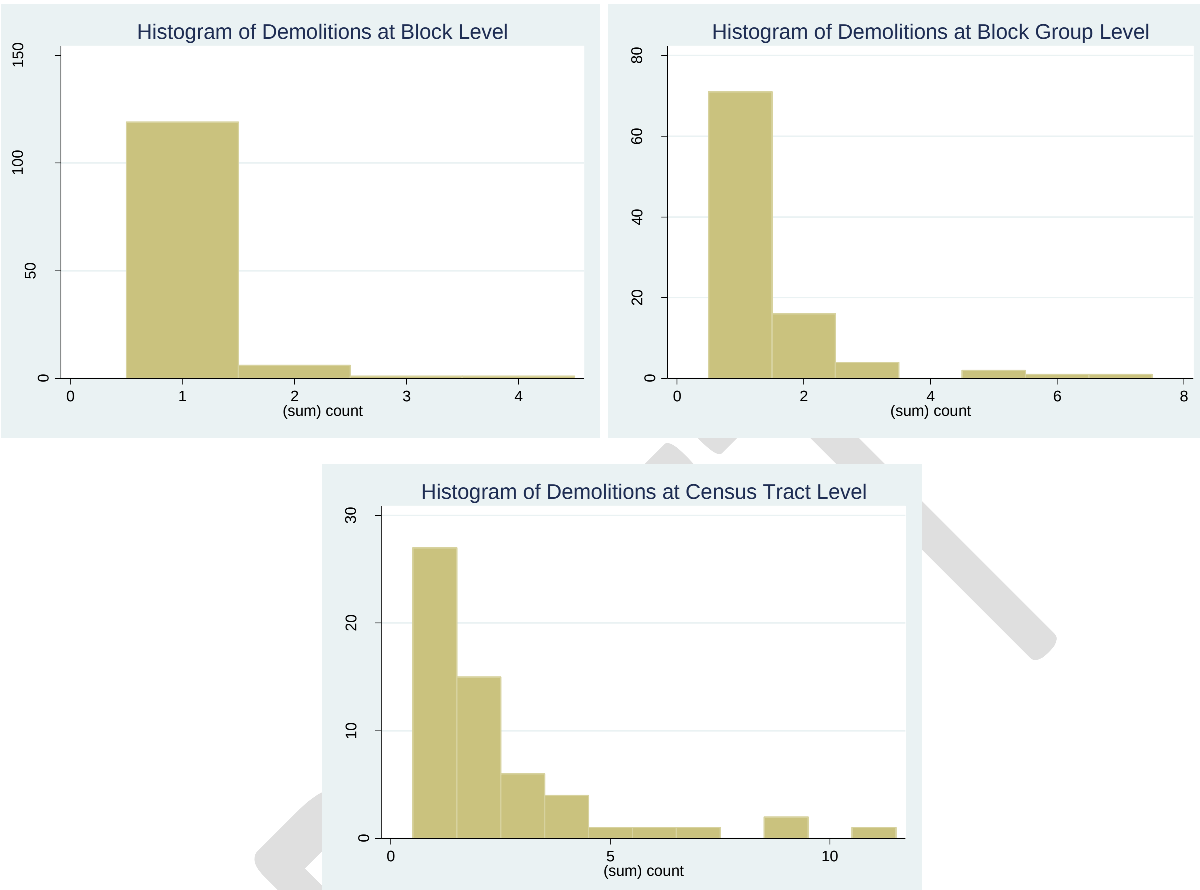
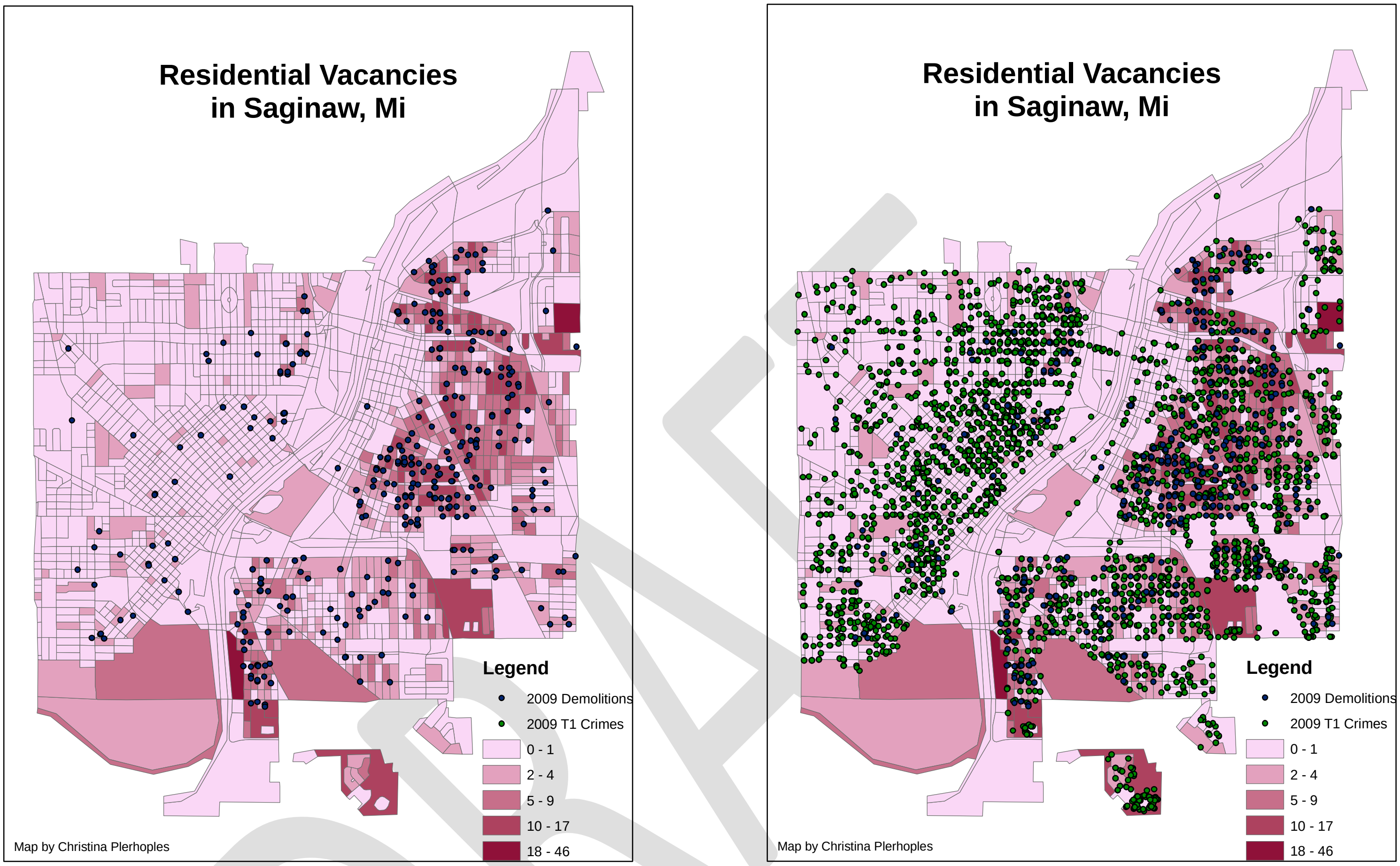


Figure 4, illustrates the data geographically. Both maps show the density of vacant parcels in Saginaw in 2009 in the underlying colors of the chloropleth (the darker the block, the more vacant it is). The first map show the demolitions that took place in 2009 and the second one adds to that the type one crimes only that took place in that same year. Type one crimes are more serious crimes as defined by the FBI.

Figure 4: Density of residential vacancies in Saginaw, Michigan 2009 with demolitions and type 1 crimes

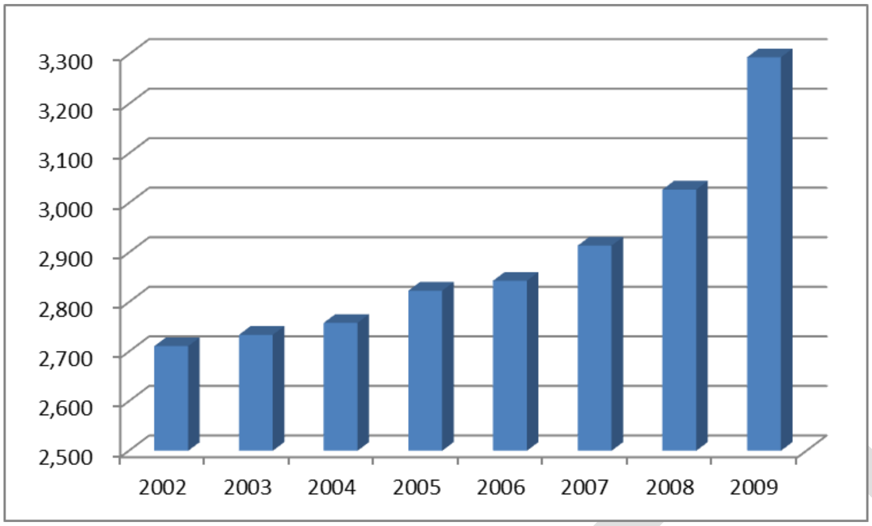


A. Brief Background on Saginaw

Saginaw has undergone rapid depopulation since the decline of manufacturing in the latter half of the 20th century. Foreclosures and land vacancies that had already been increasing were exacerbated by the financial and housing crises of 2007 as can be seen in Figure 5. Crime is also a serious problem. As mentioned previously, Saginaw ranked as the most violent city in America from 2003 through September of 2008.[29]

[29] Burns, 2010

Figure 5: Total residential vacancies in Saginaw, Michigan, 2002-2009



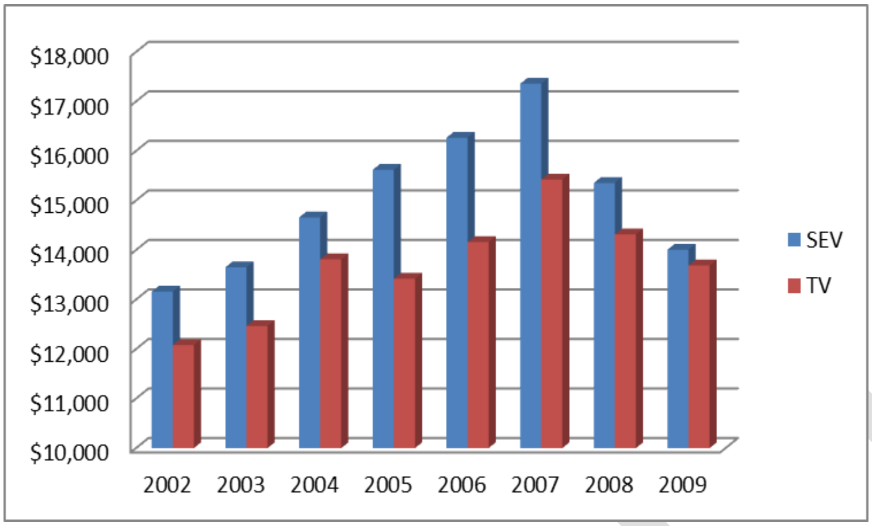
Property values have decreased substantially from an already depreciated level since the financial crisis of 2007, as illustrated in Figure 6. Home appreciation in 2009 in Saginaw was -10.3% and the unemployment rate reached as high as 19.7%.[30] Because of the lag between the time when a home loses value and when its official assessed value decreases, property values will continue to feel the effect of both the recession and depopulation long after they have both subsided.[31] Because of these issues, the municipal consulting firm Plante & Moran projects that the city of Saginaw could face a $19.9 million deficit by 2014 if leaders do not adjust to declining revenues and a shrinking population.[32]

[30] Sperlings, 2009

[31] Since the approval of the General Property Tax Act in 1893, property taxes have been the main source of revenue for local governments in Michigan. However, the property tax structure was altered in 1994 by Proposal A which placed a constitutional cap on the growth of taxable value (TV). Since Proposal A was instated, the TV of a property has been allowed to increase only by the lesser of the rate of inflation or five percent until the property is transferred (not including additions or new construction). Historically, this value has been below the state equalized value (SEV) which has led to a general decline in property tax revenues as a proportion of property values. It was not anticipated that the SEV would begin to decrease and eventually fall below TV as has already occurred for some properties throughout the state. When this happens, the property tax paid by the owner follows the fall in SEV. In the short-run, Proposal A may help to insulate local revenues from the declining home values. However, when house prices do stabilize and begin to increase, TV will be ratcheted downward and local unit fiscal capacity may not recover for years.

[32] Engel, 2010

Figure 6: Average residential taxable and State Equalized Values (SEV) in Saginaw, Michigan, 2002-2009



B. Demolition Process

Demolitions are a key part of Saginaw policy relating to vacant and abandoned buildings. To implement demolitions, Saginaw utilizes both Community Development Block Grant (CDBG) and Neighborhood Stabilization Program (NSP) funds provided by the US Department of Housing and Urban Development (HUD). The buildings that Saginaw demolishes need not be vacant; they only need to be qualified as dangerous. They could be owned by private individuals, corporations, limited liability companies, mortgage companies, the county treasurer, or the county land bank. The city does not take ownership of the property; it only enforces its right and obligation to keep the city safe. Once demolished, the property value drops to the current local value for a vacant lot of equal size.

Once a building is put on the dangerous building list, it is demolished in numerical order. There are several ways in which a property can be placed on the dangerous building list. The first is through a resident complaint filed with the city's complaint department or clerk's office. Complaints are anonymously received and entered into the complaint system. Once entered, the complaints go to the appropriate department and are assigned to an inspector for investigation. If the property is found to meet the city's definition of a dangerous building, then it is added to the database for further processing.[33]

The second way in which a building can be added to the dangerous buildings list is through an internal complaint from a city worker who observed the property firsthand while in the field or received complaints at a neighborhood meeting. These are checked against the database to see if there is already a case for it and if not the property is inspected to verify the allegations and then added to the list.

The third way is through citywide sweeps that are performed by the inspections department each spring and sometimes in the fall. During these sweeps, inspections department personnel take one day to drive up and down every street within the city limits looking for any and all visible code violations. These violations are noted for further action.

If a building undergoes arson, it is immediately demolished. I utilize this information to examine the endogeneity of demolitions and crime within Saginaw. I also exclude emergency demolitions and arson caused demolitions from the causal analysis.

C. Data Trends and Identification

Identification of the effect of demolitions on crime requires that the endogeneity associated with crime affecting the location and timing of demolitions is controlled for. Blocks that undergoe demolitions are statistically different from blocks that never undergoe a demolition both in terms of demographic characteristics and crime counts as can be seen in Figures 7 and 8.[34] This leads to inconsistent estimates if using a cross section of blocks as can be seen in Figure 9. These effects can be misleading and one may wrongly assume that demolitions cause an increase in crime when in fact it is the higher levels of crimes, or variables correlated with higher levels of crime, that induce vacancy and demolition.

[33] Personal correspondence with Scott Crofoot, Saginaw Dangerous Buildings Inspector

[34] A complete list of demographics and mean tests can be found in Appendix A

Figure 7: Selected demographic characteristics and mean difference tests for blocks with and without demolitions

	Blocks with no Demolitions	Blocks with >0 Demolitions	Difference	P-Value
Population	32.542	39.679	-7.136	0.044
	(0.876)	(2.679)		
White	16.023	8.036	7.987	0.001
	(0.581)	(0.892)		
Black	13.369	27.500	-14.131	0.000
	(0.614)	(2.414)		
Males	15.202	17.902	-2.700	0.120
	(0.431)	(1.169)		
Females	17.341	21.777	-4.436	0.025
	(0.489)	(1.571)		
Median Age	25.767	27.140	-1.373	0.388
	(0.397)	(0.932)		
Number of Households	12.286	13.705	-1.419	0.309
	(0.347)	(0.976)		
Average Household Size	2.110	2.770	-0.660	0.000
	(0.031)	(0.082)		
Owner Occupied Housing	7.891	7.473	0.418	0.658
	(0.237)	(0.454)		
Renter Occupied Housing	4.395	6.232	-1.837	0.038
	(0.217)	(0.787)		
Vacant	1.253	2.205	-0.952	0.000
	(0.051)	(0.198)		
Size	273794.600	214886.000	58908.600	0.389
	(17201.890)	(20797.640)		

Standard errors are listed in parentheses below the means

Figure 8: Crime statistics and mean difference tests for blocks with and without demolitions

	Blocks with no Demolitions	Blocks with > 0 Demolitions	Difference	P-Value
All Crimes	0.237	0.274	-0.037	0.007
	(0.003)	(0.013)		
All Crimes Sans Arson	0.23	0.258	-0.028	0.035
	(0.003)	(0.012)		
Violent Crimes	0.048	0.061	-0.013	0.02
	(0.001)	(0.005)		
Property Crimes	0.117	0.131	-0.014	0.119
	(0.002)	(0.009)		
Property Crimes Sans Arson	0.117	0.131	-0.014	0.119
	(0.002)	(0.009)		

Standard errors are listed in parentheses below the means

Figure 9: Cross Section Ordinary Least Squares of Demolitions on Crime

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Demolitions	0.508**	0.192*	0.151
	(0.240)	(0.102)	(0.136)
Observations	1,869	1,869	1,869
R-squared	0.001	0.001	0

Robust standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a cross section of all blocks in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents on each block in each month.

To control for this endogeneity, I utilize both a panel analysis which allows me to compare a block to itself over time, and a quasi-experimental design in which I compare blocks that have a demolition in that month to blocks that have a permit for a demolition in that month. Crime on blocks with demolitions in that month and blocks with permits in that month are not statistically different from one another as can be seen in figure 10.[35]

[35] I cannot compare the demographic characteristics of blocks that have a permit versus blocks that have a demolition because I do not have time-varying demographics data and all blocks that have a permit eventually get demolished so there would be no difference between the two.

Figure 10: Crime statistics and mean difference tests for block/months with a permit versus those with a demolition

	Blocks with Permits	Blocks with Demolitions	Difference	P-Value
All Crimes	0.313	0.242	0.071	0.221
	0.015	0.042		
All Crimes Sans Arson	0.289	0.219	0.070	0.205
	0.015	0.041		
Violent Crimes	0.077	0.050	0.027	0.282
	0.007	0.019		
Property Crimes	0.169	0.123	0.046	0.277
	0.011	0.032		
Property Crimes Sans Arson	0.169	0.123	0.046	0.277
	0.169	0.123		

Standard errors are listed in parentheses below the means

These statistics support the use of blocks with a permit as a control group for blocks with a demolition. However, there might still be concern within the permit list the order of demolitions is in part determined by the trajectory of crime on that block. The key identification assumption for the exogeneity of demolitions and crime is that demolitions are not correlated with unobserved factors that influence the change in crime rates. In order to examine this further, I split blocks with demolitions into those that had a demolition in 6 months or less of having a permit for that demolition (fast demolition) and those that had a demolition more than 6 months after having a permit for that demolition (slow demolition). I then compare the average change in crime on these blocks between the time that the permit was issued and the demolition was undertaken. Figure 11 shows these results which indicate that that the trajectory of crime on blocks with a fast demolition is not statistically different from blocks with a slow demolition, providing evidence that permitted blocks are a suitable control group for blocks with demolitions.

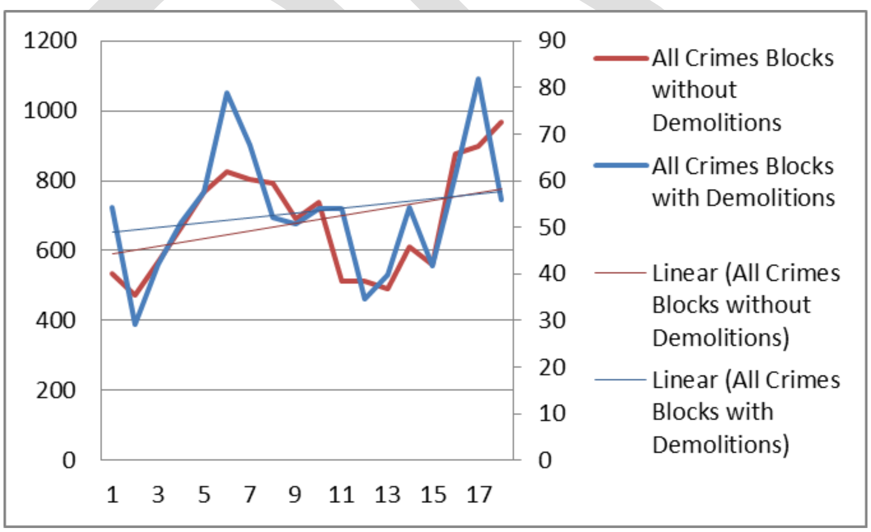
Figure 11: Crime statistics and mean difference tests for block/months with a fast demolition versus those with a slow demolition

	Fast Demos (130 Obs.)	Slow Demos (319 Obs.)	Difference	P-Value
Change in All Crimes	0.003	0.000	0.003	0.971
	(0.953)	(0.629)		
Change in All Crimes Sans Arson	0.003	-0.012	0.014	0.851
	(0.953)	(0.621)		
Change in Violent Crimes	0.020	-0.001	0.021	0.554
	(0.414)	(0.297)		
Change in Property Crimes	-0.023	0.001	-0.024	0.669
	(0.650)	(0.500)		
Change in Property Crimes Sans Arson	-0.023	0.001	-0.024	0.669
	(0.650)	(0.500)		

Standard errors are listed in parentheses below the means

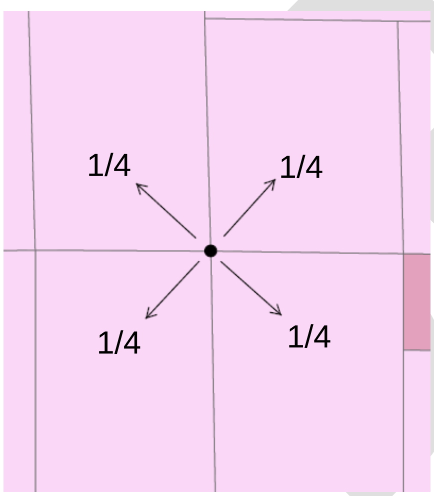
Another concern may be that if crime decreased or increased throughout the entire city during the time period of the study, then the effect of a demolition may be picking up some of this effect. Figure 12 shows that crime increased slightly during the time period and compares the trends in crime on blocks with demolitions and those without demolitions. Blocks without demolitions have a slightly larger linear increase in crime during the time period.

Figure 12: Crimes on blocks with and without demolitions



I performed four manipulations to the data. First, I removed non-criminal incidents such as traffic violations which are not relevant for the analysis. Second, I removed incidents that were follow up reports so as to not double count crimes and to ensure that correct date is assigned to each crime. Third, I removed all emergency demolitions since these are directly caused by crime (arson) as stated previously. Fourth, I assigned crimes that occurred at an intersection or on a street equally to the blocks that they touched. For instance, if a crime occurred at the intersection of four blocks, I assigned ¼ of that crime to each adjacent block as is illustrated in figure 13. These crimes at intersections are not a trivial percentage of crimes. Out of the 20,412 crimes in the data set, 3,709 or 18% occurred on streets or at intersection. This includes 9 homicides, 1 murder, and a number of robberies and assaults with weapons. Therefore it is important to include these in the analysis in a way that minimizes the bias caused from their location. However, these crimes may bias results at the block level which is important to keep in mind when interpreting results at the block level. Results at the block group and census tract level should be less sensitive to this bias.

Figure 13: Assignment of Crimes at Intersections



5 Results

Results indicate that demolitions do decrease crime on the block of the demolition, but that the aggregate effect on the census tract as a whole is null. Demolitions also cause a slight increase in violent crime at the block group level, indicating that there may be some spatial and type of crime displacement.

Figure 14 shows the average number of crimes before a permit, during the permit period, and after a demolition on the blocks in the city that had a demolition during the data period. Figre 15 plots these averages. The permit period is associated with a slight increase in all crime and an increase in violent crime, but a decrease in property crime and the post demolition period is associated with a slight decrease in all crime, a slight increase in violent crime, and a slight decrease in property crime. However, these simple averages do not control for block or month fixed effects and since a large portion of the demolitions occurred in the winter, these averages could reflect seasonal changes in crime.

Figure 14: Average number of crimes on each block in each month pre-permit, during permit, and post-demolition

	Pre-Permit	Permit	Post-Demo	Blocks with a Demo, All Months	All Blocks, All Months
All Crime	0.26	0.28	0.27	0.26	0.24
Violent Crime	0.04	0.06	0.07	0.06	0.05
Property Crime	0.14	0.13	0.12	0.12	0.12

Figure 15: Average number of crimes before a permit, during permit period, and after a demolition

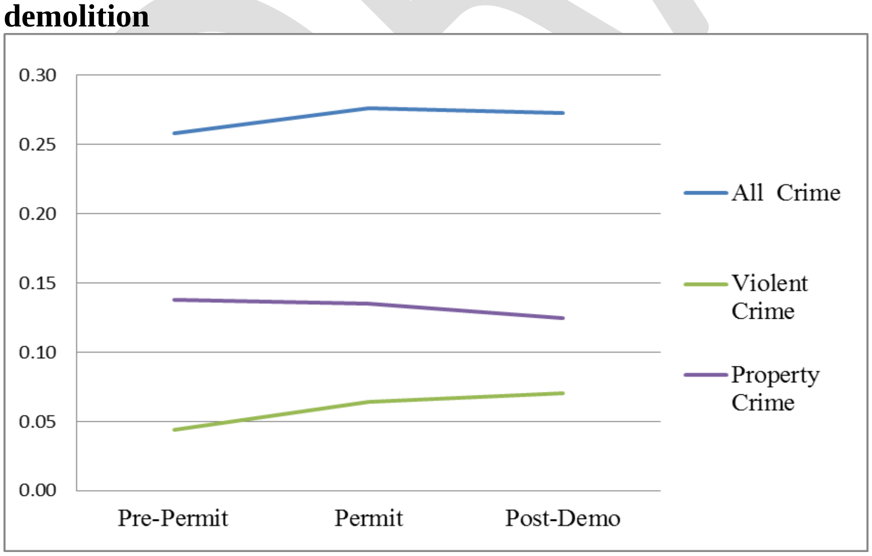
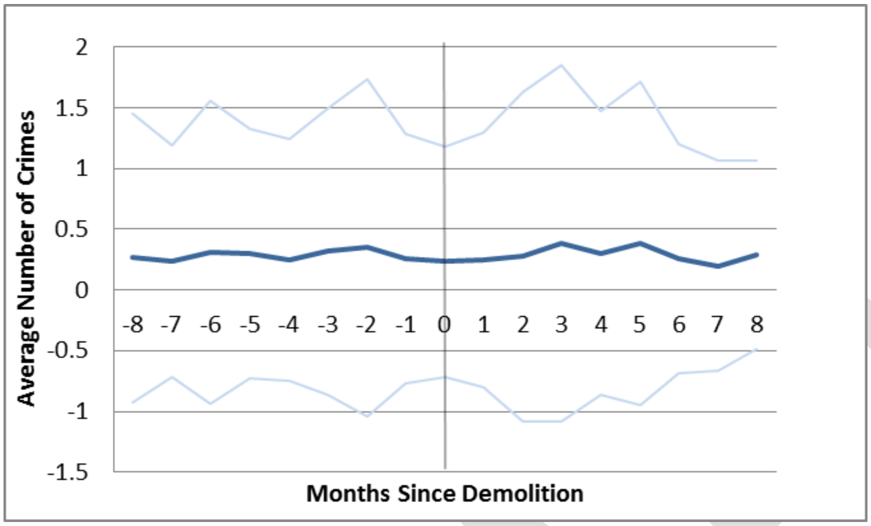


Figure 16 plots the average number of crimes before and after a demolition. Once again, little effect can be seen here, but this does not control for block or month fixed effects either.

Figure 16: Average number of crimes on a block before and after a demolition



Once we control for block and month fixed effects (which removes unobserved heterogeneity), we see more effects. Figure 17 shows the results of the base model where demolitions and permits are regressed on crime with no time lags. Demolitions and permits are specified as stock variables, or the cumulative number of permits and demolitions on a block. These results indicate that permits demolitions are correlated with a reduction in property crime of 32.7%. In order to causally interpret this, I compare this effect to the effect permits on crime at the block level and find that one demolition causes a reduction in property crime of 49.1%. Since the average number of property crimes per month on blocks that undergo a demolition at some point during the sample is 0.115 crimes, a 49.1% reduction in this number is 0.056 crimes per month. On an annual basis, this equates to a reduction of 0.678 property crimes per year. No clear effect can be seen for all crimes or violent crimes at the block level.

Figure 17: Poisson fixed effects results at the block level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Permits	0.049	-0.124	0.164
	(0.085)	(0.148)	(0.108)
Demolitions	-0.176	-0.089	-0.327*
	(0.112)	(0.198)	(0.191)
Demolitions-Permits	-0.225	0.036	-0.491**
	(0.153)	(0.268)	(0.239)
Observations	28,656	17,496	23,040
Number of Blocks	1,592	972	1,280

Robust standard errors in parentheses, clustered at the block level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all blocks in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents on each block in each month.

These results may be biased by the way that I distributed crimes at intersections. Because of this and in order to understand the aggregate effect of demolitions on crime, I also aggregate the data to the block group and census tract levels to see how overall crime is changed when a demolition occurs. Figure 16 gives the results for the block group level aggregation. This tells us how demolitions effect crime in the neighborhood as a whole. Demolitions are correlated with an increase in all crime of 1.4% and an increase in property crime of 2.5%. However, once this effect is compared to the control group (the permit period), only the effect on violent crime is statistically significant. One demolition causes an increase in violent crime at the block group level of 5.1%. There average number of violent crimes on blocks with a demolition during the data period is 0.06 crimes per month. A 5.1% change in this number is 0.003 violent crimes per month, or 0.037 crimes per year. Therefore, a demolition causes an increase of 0.037 crimes per year in the neighborhood of a demolition. This could be due to spatial and type of crime displacement, in which criminals switch from property crime on the block of the demolition to violent crime on other blocks near to the demolition.

Figure 16: Poisson fixed effects results at the block group level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Permits	0.007	-0.0266**	0.0300**
	(0.007)	(0.013)	(0.013)
Demolitions	0.014**	0.025**	0.006
	(0.007)	(0.011)	(0.009)
Demolitions-Permits	0.007	0.051***	-0.024
	(0.011)	(0.019)	(0.018)
Observations	1,314	1,296	1,314
Number of Block Groups	73	72	73

Robust standard errors in parentheses, clustered at the block group level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all block groups in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each block group in each month.

At the census tract level, no clear effect of demolitions can be seen on any type of crime. This suggests that the overall, aggregate effect of demolitions on crime is null and that crime is merely displaced from one location to another when a demolition occurs. These results can be seen in Figure 17.

Figure 17: Poisson fixed effects results at the census tract level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Permits	0.002	-0.005	0.008
	(0.003)	(0.004)	(0.006)
Demolitions	0.000	0.001	-0.003
	(0.003)	(0.004)	(0.006)
Demolitions-Permits	-0.001	0.006	-0.011
	(0.006)	(0.005)	(0.011)
Observations	360	342	360
Number of Census Tracts	20	19	20

Robust standard errors in parentheses, clustered at the census tract level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all census tracts in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each census tract in each month.

To explore the displacement and spillover effects further, I regress demolitions on crime and include two spatial lags for demolitions: one at the block group and one at the census tract level. This tells me how crime varies at the block level when a demolition occurs on the block, in the block group, or in the census tract, holding the others constant. These results can be seen in Figure 18. Once again we see a decrease in property crime at the block level, an increase in violent crime at the block group level, and no effect at the census tract level. This implies that negative displacement is occurring in which criminals are switching between property and violent crime and moving into surrounding areas within the neighborhood of the demolition. This could be because they are no longer able to commit the crime that they were previously committing now that the building is gone, so they switch to a different type of crime and to a different location.

Figure 18: Poisson fixed effects results at the block level with two spatial lags

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Permits on Block	0.035	-0.092	0.126
	(0.086)	(0.148)	(0.108)
Demolitions on Block	-0.206*	-0.130	-0.338*
	(0.110)	(0.199)	(0.194)
Demolitions-Permits on Block	-0.241	-0.038	-0.463*
	(0.152)	(0.266)	(0.240)
Permits in Block Group	0.009	-0.027	0.028**
	(0.009)	(0.017)	(0.014)
Demolitions in Block Group	0.021**	0.029*	0.023
	(0.009)	(0.015)	(0.016)
Demolitions-Permits in Block Group	0.011	0.056**	-0.006
	(0.015)	(0.025)	(0.024)
Permits in Census Tract	0.000	0.007	0.001
	(0.004)	(0.010)	(0.006)
Demolitions in Census Tract	-0.005	-0.012	-0.006
	(0.004)	(0.008)	(0.007)
Demolitions-Permits in Census Tract	-0.005	-0.019	-0.006
	(0.007)	(0.015)	(0.011)
Observations	28,656	17,496	23,040
Number of objectid	1,592	972	1,280

Robust standard errors in parentheses, clustered at the block level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all blocks in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents on each block in each month.

Figures 19, 20, and 21 graphically display the coefficients and their 95% confidency intervals for the event study that details the monthly dynamics of the effect of demolitions on crime.[36] These are the results of a regression of two leads and 6 lags of demolitions on crime for blocks that have a demolition at some point during my data period. Demolitions are specified

[36] Standard regression output for these graphs can be found in Appendix B.

here as flow variables in which the variable turns to one during the month of a demolitions and then returns to zero in the months after the demolition. Similar to the contemporaneous analysis, I perform this at the block level, at the block group level, and finally at the census tract level. Comparing the effect before the demolition (when a permit is in place) to the results after a demolition, little visible effect can be seen at the block level (aside from a slight spicke in all crime two months after a demolition), and very little at the block group or census tract level as well. Some long term effects appear to be present, but these may be picking p seasonal effects because of the limited number of blocks that have a demolition more than six months prior to the current month.

Figure 19: Poisson fixed effects event study results at the block level

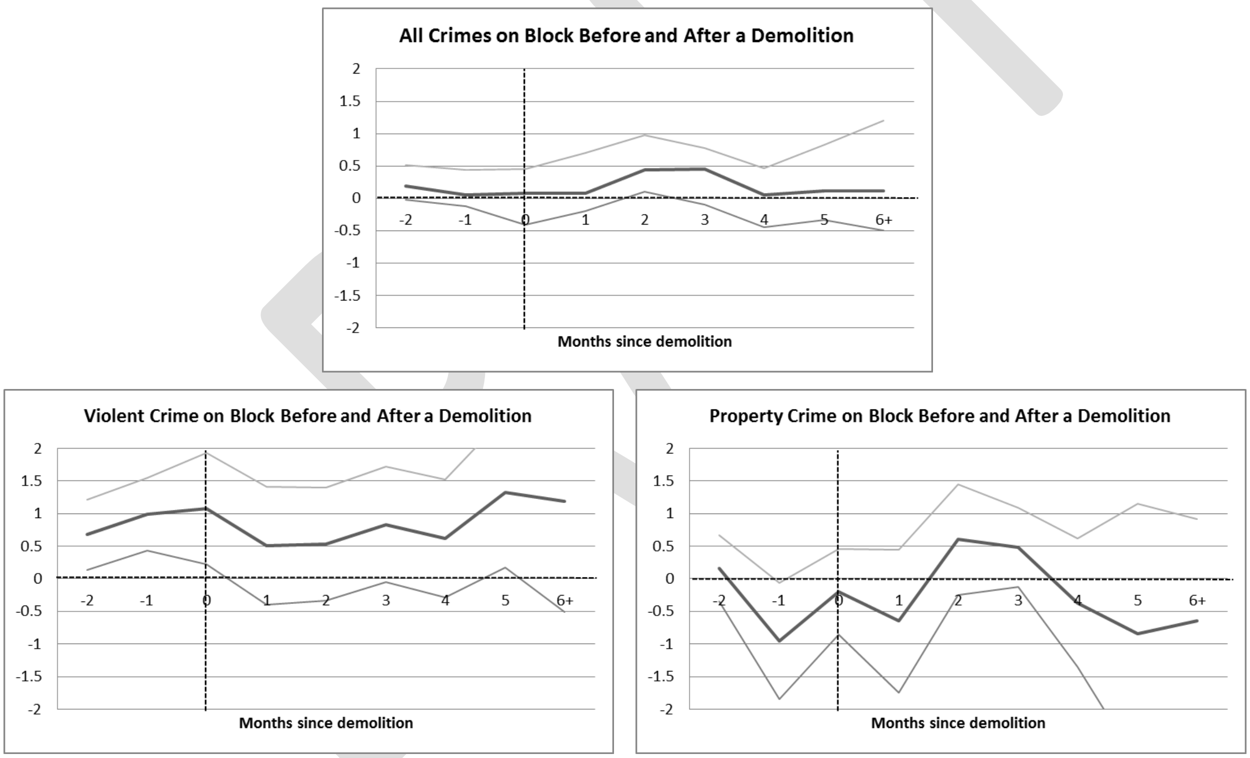


Figure 20: Poisson fixed effects event study results at the block group level

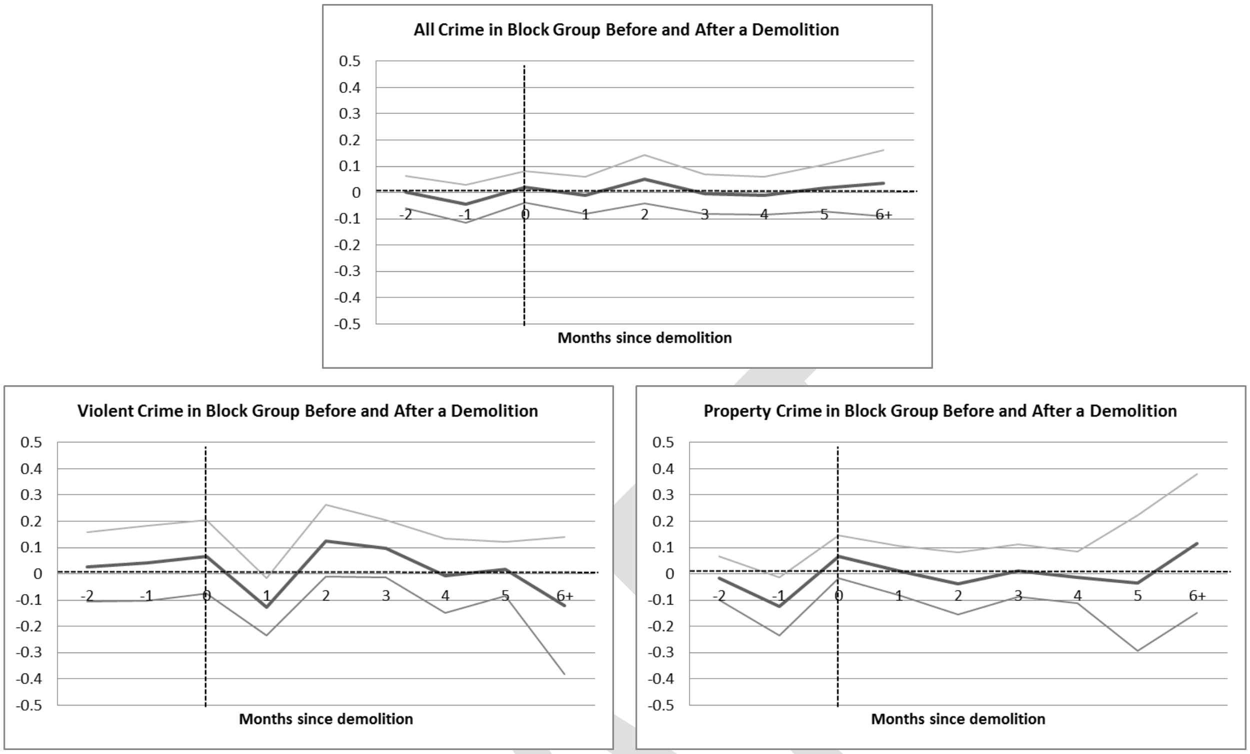
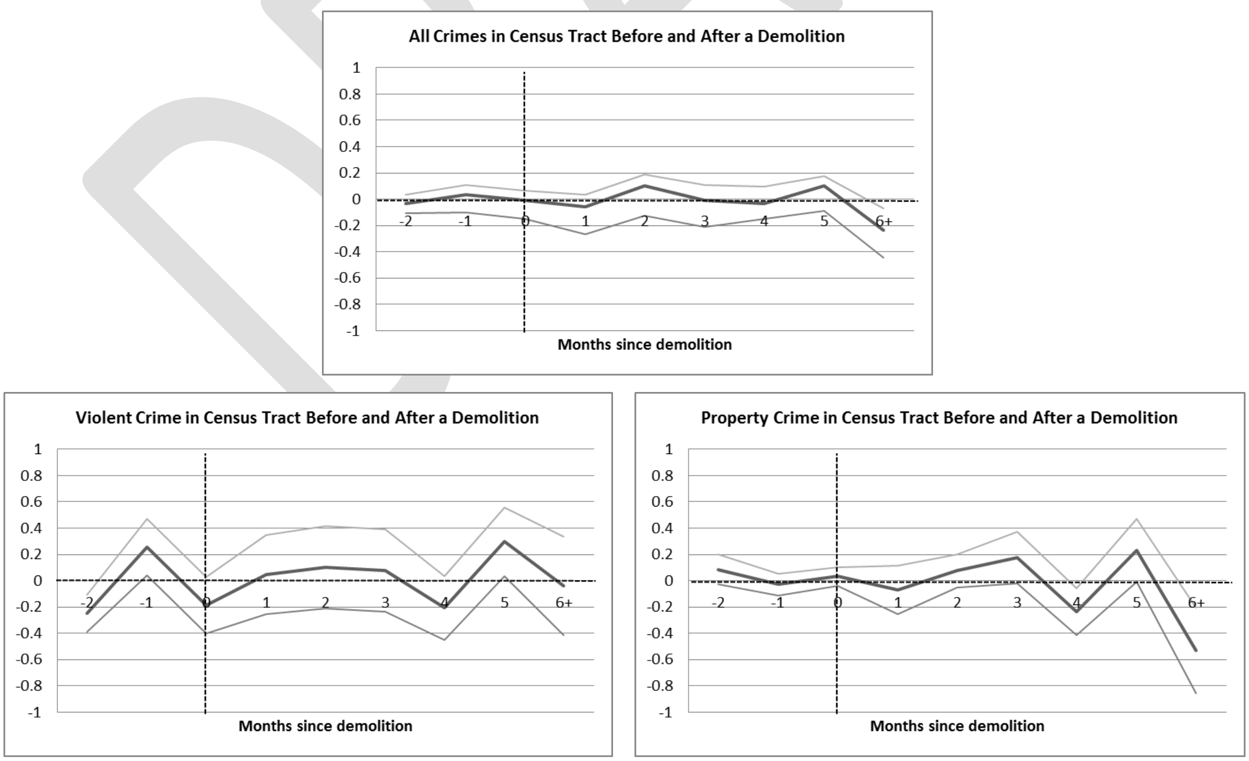


Figure 21: Poisson fixed effects event study results at the census tract level



6 Conclusion

Millions of dollars are spent each year demolishing vacant homes with an often cited justification being that demolitions reduce crime. However, no previous research sufficiently identifies the causal effect of residential demolitions on crime. This paper is the first to identify this change using a quasi-experimental panel data approach with results indicating that one demolition causes a reduction in property crime of 49.1% or 0.056 crimes per month. On an annual basis, this equates to a reduction of 0.678 property crimes per year. However, this reduction at the block level is offset by an increase in crime at the block group level. One demolition at the block group level causes an increase in violent crime of 5.1% or 0.003 violent crimes per month. Therefore, a demolition causes an increase of 0.037 crimes per year in the neighborhood of a demolition. This could be due to spatial and type of crime displacement, in which criminals switch from property crime on the block of the demolition to violent crime on other blocks near to the demolition.

The aggregate, census tract level effect of vacant building demolitions on crime appears to be zero, suggesting that the true effect of a demolition on crime is merely to displace it within a census tract rather than reduce the overall level of crime. This calls to question the effectiveness of demolitions at reducing crime if the policy goal is to reduce overall crime within a city. The average cost de-construction cost of a demolition in Saginaw is $5,020.58. Therefore, it costs $7404.98 to reduce one property crime a year at the block level. This does not include the overhead costs of the city demolition department nor the US Department of Housing and Urban Development which funds many of the demolitions. This reduction is then partially offset by an increase in violent crimes on surrounding blocks.

Although this does not appear to be a cost effective policy, there are other hypothesized benefits associated with demolitions such as higher property values for parcels surrounding a demolition as well as reduced risk of injury related from removing an unsound structure. [37] These results also do not account for the effect of demolitions on arson which should be examined separately in relation to the structure of demolition policy. However, overall, the benefits of demolitions related to crime reduction appear to be not worth the cost and demolitions should therefore not be thought of as a substitute for public safety services.

[37] Griswold, 2006

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Appendix A: Additional Demographics

Figure A1: Demographic characteristics and mean difference tests for blocks with and without demolitions

	Blocks with no Demolitions	Blocks with >0 Demolitions	Difference	P-Value
Population	32.542	39.679	-7.136	0.044
	(0.876)	(2.679)		
White	16.023	8.036	7.987	0.001
	(0.581)	(0.892)		
Black	13.369	27.500	-14.131	0.000
	(0.614)	(2.414)		
American indian and Alaska Native	0.158	0.214	-0.057	0.379
	(0.016)	(0.074)		
Asian	0.116	0.018	0.098	0.175
	(0.018)	(0.013)		
Native Hawaiian and Other Pacific Islander	0.006	0.000	0.006	0.572
	0.003	0.000		
Other	1.877	2.804	-0.927	0.007
	(0.082)	(0.413)		
Two or More Races	0.994	1.107	-0.113	0.568
	(0.048)	(0.193)		
Hispanic	3.775	5.464	-1.689	0.002
	(0.131)	(0.573)		
Males	15.202	17.902	-2.700	0.120
	(0.431)	(1.169)		
Females	17.341	21.777	-4.436	0.025
	(0.489)	(1.571)		
Under 5 years	2.782	3.830	-1.048	0.024
	(0.115)	(0.384)		
Age 5 to 17	7.355	11.054	-3.698	0.000
	(0.222)	(0.916)		
Age 18 to 21	1.921	2.223	-0.302	0.329
	(0.077)	(0.197)		
Age 22 to 29	3.737	4.286	-0.548	0.292
	(0.129)	(0.373)		
Age 30 to 39	4.476	5.116	-0.640	0.244
	(0.136)	(0.424)		
Age 40 to 49	4.595	4.991	-0.396	0.449
	(0.130)	(0.380)		
Age 50 to 64	3.895	4.536	-0.640	0.192

	(0.122)	(0.313)		
Age 65 and up	3.780	3.643	0.137	0.837
	(0.166)	(0.289)		
Median Age	25.767	27.140	-1.373	0.388
	(0.397)	(0.932)		
Median Age Males	23.965	24.210	-0.245	0.877
	(0.395)	(1.063)		
Median Age Females	26.550	28.543	-1.992	0.235
	(0.418)	(1.050)		
Number of Households	12.286	13.705	-1.419	0.309
	(0.347)	(0.976)		
Average Household Size	2.110	2.770	-0.660	0.000
	(0.031)	(0.082)		
Households of 1 Male	1.616	1.679	-0.062	0.819
	(0.068)	(0.168)		
Households of 1 Female	2.043	1.884	0.159	0.696
	(0.102)	(0.212)		
Married Households with Children	1.771	1.357	0.414	0.098
	(0.063)	(0.122)		
Married Households with no Children	2.347	1.875	0.472	0.152
	(0.082)	(0.157)		
Male Headed Household with Children	0.310	0.357	-0.047	0.437
	(0.015)	(0.015)		
Female Headed Household with Children	2.228	3.830	-1.602	0.000
	(0.106)	(0.450)		
Number of Families	7.960	9.563	-1.602	0.079
	(0.226)	(0.701)		
Average Family Size	2.481	3.311	-0.830	0.000
	(0.036)	(0.097)		
Household Units	13.540	15.911	-2.371	0.111
	(0.369)	(1.057)		
Owner Occupied Housing	7.891	7.473	0.418	0.658
	(0.237)	(0.454)		
Renter Occupied Housing	4.395	6.232	-1.837	0.038
	(0.217)	(0.787)		
Vacant	1.253	2.205	-0.952	0.000
	(0.051)	(0.198)		
Size	273794.600	214886.000	58908.600	0.389
	(17201.890)	(20797.640)		

Standard errors are listed in parentheses below the means

Appendix B: Event Study Regression Results

Figure B1: Poisson event study regression results at the block level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Second lead of demolitions	0.189	0.678**	0.165
	-0.167	-0.274	-0.259
First lead of demolitions	0.055	0.990***	-0.957**
	-0.197	-0.286	-0.455
Demolitions	0.081	1.076**	-0.197
	-0.188	-0.439	-0.335
First lag of demolitions	0.078	0.508	-0.649
	-0.318	-0.459	-0.560
Second lag of demolitions	0.439	0.528	0.602
	-0.273	-0.443	-0.433
Third lag of demolitions	0.454***	0.834*	0.481
	-0.165	-0.449	-0.311
Fourth lag of demolitions	0.054	0.623	-0.370
	-0.207	-0.461	-0.502
Fifth lag of demolitions	0.113	1.329**	-0.843
	-0.366	-0.593	-1.019
Six plus lags of demolitions	0.117	1.185	-0.649
	-0.552	-0.866	-0.795
Observations	1,122	682	770
Number of Blocks	102	62	70

Robust standard errors are in parentheses, clustered at the block level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all blocks in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents on each block in each month.

Figure B2: Poisson event study regression results at the block group level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Second lead of demolitions	0.003	0.027	-0.018
	(0.031)	(0.068)	(0.042)
First lead of demolitions	-0.043	0.041	-0.125**
	(0.037)	(0.073)	(0.056)
Demolitions	0.022	0.065	0.066
	(0.031)	(0.071)	(0.041)
First lag of demolitions	-0.011	-0.126**	0.012
	(0.036)	(0.056)	(0.048)
Second lag of demolitions	0.051	0.126*	-0.037
	(0.047)	(0.070)	(0.060)
Third lag of demolitions	-0.006	0.0963*	0.012
	(0.039)	(0.056)	(0.051)
Fourth lag of demolitions	-0.011	-0.007	-0.013
	(0.036)	(0.072)	(0.050)
Fifth lag of demolitions	0.017	0.019	-0.035
	(0.046)	(0.053)	(0.132)
Six plus lags of demolitions	0.035	-0.122	0.116
	(0.064)	(0.133)	(0.135)
Observations	550	550	550
Number of Block Groups	50	50	50

Robust standard errors are in parentheses, clustered at the block group level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all block groups in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each block group in each month.

Figure B3: Poisson event study regression results at the census tract level

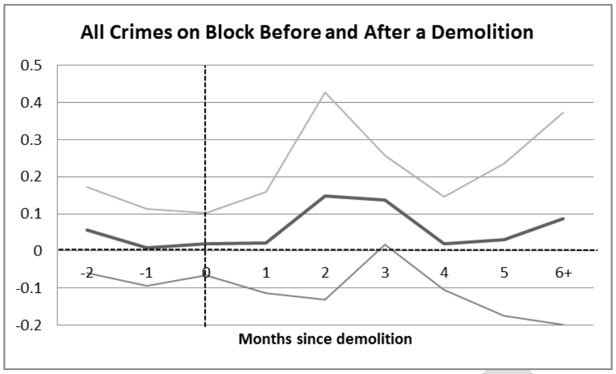
	(1) All Crime	(2) Violent Crime	(3) Property Crime
Second lead of demolitions	-0.033	-0.245***	0.085
	(0.035)	(0.072)	(0.058)
First lead of demolitions	0.034	0.257**	-0.028
	(0.039)	(0.109)	(0.043)
Demolitions	-0.007	-0.188*	0.032
	(0.035)	(0.109)	(0.035)
First lag of demolitions	-0.059	0.045	-0.069
	(0.049)	(0.154)	(0.095)
Second lag of demolitions	0.0997**	0.101	0.075
	(0.046)	(0.159)	(0.065)
Third lag of demolitions	-0.006	0.078	0.177*
	(0.057)	(0.161)	(0.101)
Fourth lag of demolitions	-0.030	-0.208*	-0.237***
	(0.063)	(0.123)	(0.091)
Fifth lag of demolitions	0.102***	0.297**	0.231*
	(0.038)	(0.134)	(0.121)
Six plus lags of demolitions	-0.233***	-0.041	-0.530***
	(0.082)	(0.191)	(0.165)
Observations	165	143	154
Number of objected	15	13	14

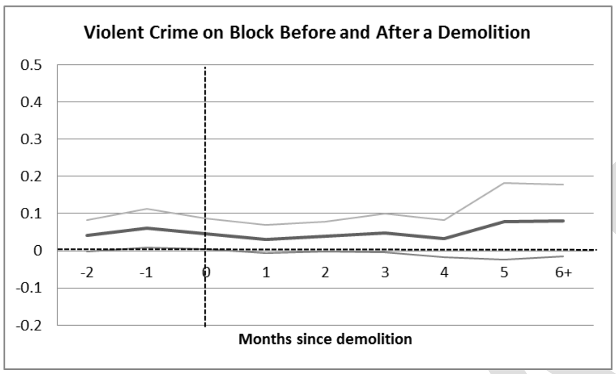
Robust standard errors are in parentheses, clustered at the census tract level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all census tracts in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each census tract in each month.

Figure B3: OLS event study regression results and graphs at the block level

	(1) All Crime	(2) Violent Crime	(3) Property Crime
Second lead of demolitions	0.056	0.0406*	0.029
	(0.059)	(0.021)	(0.039)
First lead of demolitions	0.009	0.0612**	-0.0614**
	(0.053)	(0.027)	(0.030)
Demolitions	0.019	0.0461**	-0.015
	(0.043)	(0.021)	(0.035)
First lag of demolitions	0.022	0.031	-0.026
	(0.070)	(0.020)	(0.042)
Second lag of demolitions	0.148	0.0388*	0.119
	(0.143)	(0.021)	(0.141)
Third lag of demolitions	0.138**	0.0486*	0.061
	(0.061)	(0.027)	(0.049)
Fourth lag of demolitions	0.020	0.033	0.000
	(0.064)	(0.025)	(0.043)
Fifth lag of demolitions	0.031	0.079	-0.008
	(0.105)	(0.052)	(0.056)
Six plus lags of demolitions	0.088	0.0815*	0.047
	(0.146)	(0.049)	(0.079)
Observations	1,122	682	770
Number of objected	102	62	70

Robust standard errors are in parentheses, clustered at the block level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all blocks in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents on each block in each month.


All Crimes on Block Before and After a Demolition
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-2
-1
0
1
2
3
4
5
6+
Months since demolition


Violent Crime on Block Before and After a Demolition
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-2
-1
0
1
2
3
4
5
6+
Months since demolition

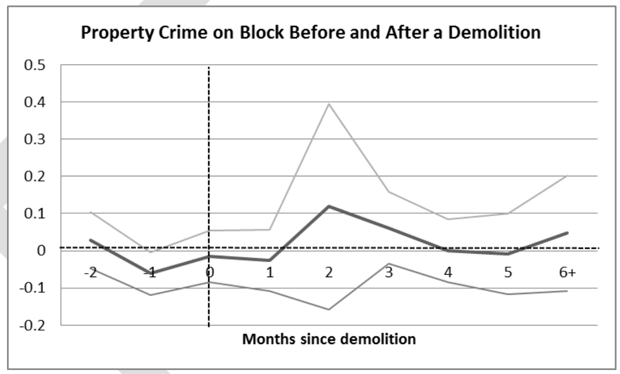
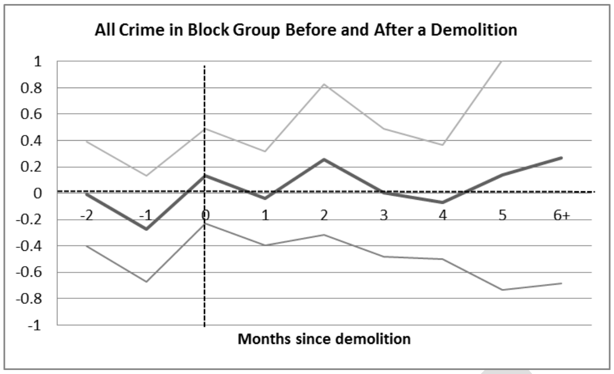
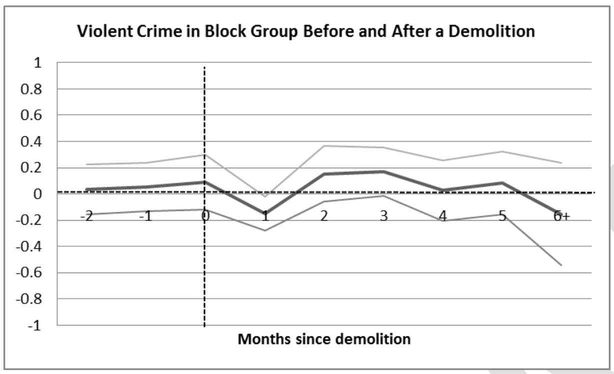

Property Crime on Block Before and After a Demolition
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-2
-1
0
1
2
3
4
5
6+
Months since demolition

Figure B3: OLS event study regression results and graphs at the block group level

	(1)	(2)	(3)
	All Crime	Violent Crime	Property Crime
Second lead of demolitions	-0.006	0.035	-0.058
	(0.201)	(0.098)	(0.132)
First lead of demolitions	-0.271	0.053	-0.300**
	(0.206)	(0.093)	(0.119)
Demolitions	0.131	0.088	0.158
	(0.183)	(0.107)	(0.108)
First lag of demolitions	-0.041	-0.150**	0.022
	(0.182)	(0.067)	(0.123)
Second lag of demolitions	0.255	0.154	-0.086
	(0.291)	(0.108)	(0.133)
Third lag of demolitions	0.003	0.167*	0.039
	(0.248)	(0.094)	(0.121)
Fourth lag of demolitions	-0.068	0.027	-0.021
	(0.221)	(0.117)	(0.127)
Fifth lag of demolitions	0.138	0.084	-0.108
	(0.445)	(0.122)	(0.407)
Six plus lags of demolitions	0.269	-0.153	0.430
	(0.486)	(0.199)	(0.382)
Observations	550	550	550
R-squared	0.206	0.114	0.14
Number of Block Groups	50	50	50

Robust standard errors are in parentheses, clustered at the block group level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all block groups in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each block group in each month.


All Crime in Block Group Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition


Violent Crime in Block Group Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition

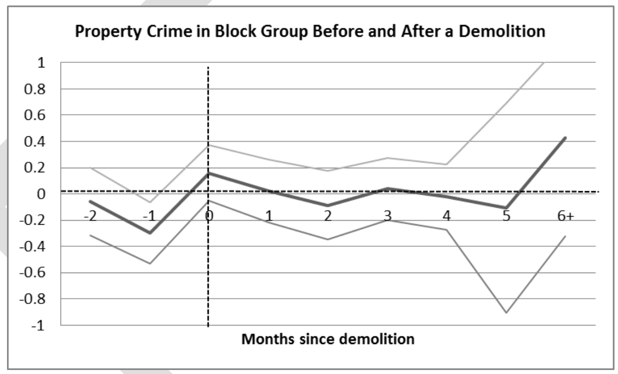
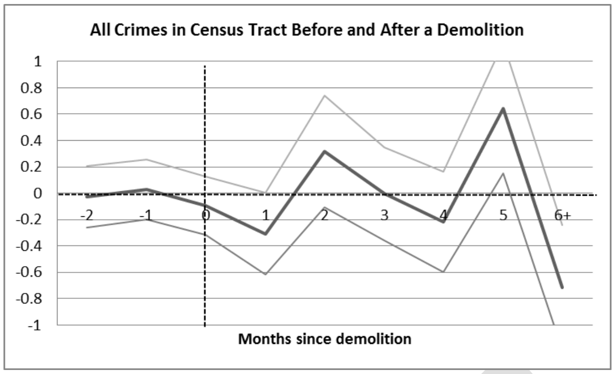
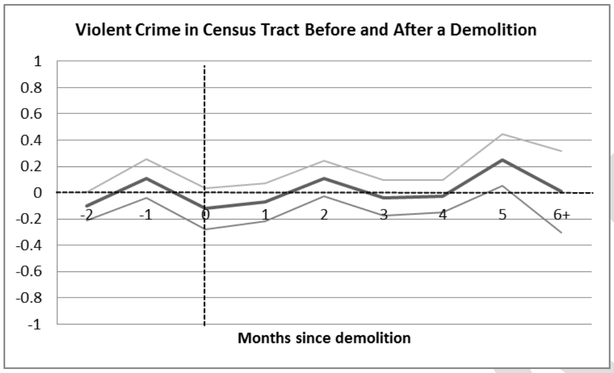

Property Crime in Block Group Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition

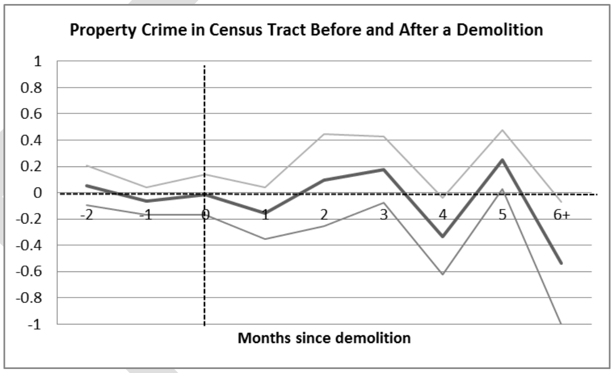
Figure B3: OLS event study regression results and graphs at the census tract level

	(1)	(2)	(3)
	All Crime	Violent Crime	Property Crime
Second lead of demolitions	-0.028	-0.103*	0.054
	(0.120)	(0.054)	(0.077)
First lead of demolitions	0.027	0.108	-0.066
	(0.116)	(0.074)	(0.053)
Demolitions	-0.095	-0.122	-0.016
	(0.112)	(0.081)	(0.079)
First lag of demolitions	-0.307*	-0.071	-0.155
	(0.159)	(0.074)	(0.100)
Second lag of demolitions	0.316	0.109	0.096
	(0.216)	(0.069)	(0.180)
Third lag of demolitions	-0.003	-0.042	0.176
	(0.180)	(0.069)	(0.129)
Fourth lag of demolitions	-0.217	-0.027	-0.332**
	(0.193)	(0.063)	(0.148)
Fifth lag of demolitions	0.645**	0.249**	0.251**
	(0.252)	(0.101)	(0.114)
Six plus lags of demolitions	-0.715***	0.007	-0.539**
	(0.240)	(0.158)	(0.238)
Observations	165	165	165
R-squared	0.316	0.285	0.265
Number of Census Tracts	15	15	15

Robust standard errors are in parentheses, clustered at the census tract level. * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is a panel of all census tracts in Saginaw, Mi from January 2008- June 2009. Crime offenses refer to the number of incidents in each census tract in each month.


All Crimes in Census Tract Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition


Violent Crime in Census Tract Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition


Property Crime in Census Tract Before and After a Demolition
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-2
-1
0
1
2
3
4
5
6+
Months since demolition